Multi-Band Radio Frequency Energy Predictor for Advanced Energy Harvesting Cellular Bands Systems

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Abstract— **Radio Frequency (RF) energy harvesting has been employed to power wireless devices. Nevertheless, RF energy harvesting encounters restrictions regarding the quantity of power it can harvest depending on signal accessibility. As a result, accurately predicting energy levels becomes crucial for enhancing the performance of energy harvesting circuits. Most research efforts have concentrated on enhancing power harvesting policies or theoretically estimating the energy obtained through RF energy harvesting. Moreover, the existing literature has primarily focused on single-band prediction approaches. This paper presents a multi-band RF energy prediction approach for RF energy harvesting systems. We collect real-time RF energy using software-defined radio technology. The proposed approach leverages Long Short-Term Memory (LSTM) neural networks to accurately predict the mean RF energy in different frequency bands for the next 100 samples, which corresponds to approximately one hour and a half. The research explores the research gap in modeling the radio frequency signal and the need for multi-band prediction techniques. The results demonstrate the effectiveness of the proposed approach in predicting RF energy across different frequency bands, with average accuracies above 98%.**

Keywords*— *Radio frequency, energy harvesting, energy prediction, multi-band, machine learning, time series model.

I. INTRODUCTION

Recent research has studied energy harvesting as the primary source of electricity in many applications. Energy harvesting refers to the process of obtaining energy from environmental sources and converting it to electrical energy for use to power other devices [1]. One popular source is radio frequency (RF) energy, which can be obtained through satellite stations, TV signals, radio waves, and Wi-Fi signals [2]. RF energy harvesting systems have attracted significant attention recently due to their potential to power wireless and low-powered devices autonomously and sustainably [3]. The significance of RF energy harvesting lies in its ability to address the challenges associated with traditional power sources such as batteries or wired connections. Batteries have some problems with increasing the size and the cost of the device. In addition, batteries require regular replacement or recharging, which can be inconvenient, costly, and environmentally unfriendly. On the other hand, wired connections may not be feasible or practical in many scenarios, especially in remote or inaccessible locations.

RF energy offers several advantages, including its widespread availability and independence from weather conditions [2]. Additionally, RF energy harvesters are compact in size anfd can be easily integrated into various devices. As a result, Radio frequency energy harvesting (RFEH) has been employed in cognitive radio networks, wireless sensor networks (WSN) [4], biomedical wearable devices [5], and Internet of Things (IoT) applications [6].

On the contrary, RF energy harvesting systems face challenges in terms of the amount of power that can be harvested based on signal availability [7], [8]. The availability and distribution of RF signals vary based on factors such as time, location, and spectrum utilization. The amount of RF energy present during working days can differ from weekends, indicating temporal variations in energy levels for specific locations. Additionally, certain frequency bands exhibit higher RF energy levels compared to others [9]. Areas with more cell phone users tend to have increased RF energy. Consequently, an effective RF energy harvesting circuit should be able to select the optimal time and optimal frequency band for energy harvesting.

In a single-band system, the RF harvester can only harvest from specific frequencies, limiting its capability to harvest from other accessible frequency bands in the environment. This limitation results in missed chances for energy harvesting, as the energy density might vary across different bands. If the ambient energy in a particular band is low, harvesting efficiency may suffer, leading to poor power output [10]. To overcome these limitations, a concept known as multiband RFEH systems has been established to satisfy the power needs and maximize the output power. These systems are designed to gather energy from multiple RF bands, enabling a more diverse and abundant energy supply. This strategy increases the system's overall performance and efficiency by expanding the range of energy-gathering capabilities [11], [12].

Consequently, accurate prediction of the available RF energy becomes crucial to optimize the performance of energy harvesting circuits. Machine learning (ML) techniques can predict the locations and timings with the highest RF energy levels, enabling better decision-making in RF energy harvesting. Multi-band prediction techniques are vital in optimizing efficiency and performance by analyzing historical data, utilizing machine learning algorithms, and forecasting energy availability. These techniques also determine the most suitable frequency bands for real-time harvesting, allowing dynamic adaptation to changing environmental conditions and efficient allocation of resources for maximum energy capture.

Motivated by the challenges faced by RF energy harvesting systems, particularly related to signal availability and limitations of single-band systems, this paper proposes a multi-band RF energy prediction approach for RFEH systems. By harnessing the advantages of multi-band harvesting, we aim to maximize energy capture potential and enhance the overall performance of energy harvesting circuits. To achieve this, we employ machine learning techniques, precisely Long Short-Term Memory (LSTM), to accurately predict RF energy availability across six different frequency bands.

The remainder of this paper is structured as follows. Section 2 provides a comprehensive literature review covering the current state of research in the field. RF data measurement, pre-processing, and the proposed model are illustrated in section 3. The obtained results for predicting RF energy are discussed in section 4. Finally, section 5 concludes the research by summarizing the findings and drawing meaningful insights.

II. Literature review

Various applications have demonstrated the effectiveness of RF energy harvesting. For instance, a designed energy harvester chip operated at -12 dBm input power and powered a microcontroller + radio SoC [13]. In addition, a configurable 2.45 GHz RF to DC power converter achieved over 20% efficiency by dynamically switching between low-power and high-power paths depending on the RF power input value [14]. In industrial applications, the Powercast P2110 harvester produced an output voltage of 5.25 V [15]. Other examples include a sensor module in a system for monitoring food quality powered by an RF energy harvester with an operating frequency of 915 MHz [16]. A 1.8 GHz RF energy harvester was intended for powering the sensor nodes in a museum monitoring system [17].

Moreover, researchers proposed an RF energy harvester operating at 2.45 GHz with 48.3% efficiency at -3 dBm input power to power an IoT-based smart sensor system [18]. In their study [19], researchers demonstrated a system capable of generating up to 133.25W of power through the simultaneous harvesting of solar and RF sources. The hybrid system effectively charged devices in wireless sensor networks with a stable voltage and current of 20.5V and 6.5A, respectively, resulting in faster and more efficient charging. Independently, the dual-band, multi-stage RF harvester circuit could operate at 2.4GHz, Wi-Fi/WLAN frequencies. Another research developed a triple-band monopole rectenna for RF energy harvesting in smart city applications. The harvester operated in the frequency range of 1.25-3 GHz. Experimental measurements confirmed an output voltage of 1.123 V at the 2.45 GHz frequency [20].

Machine learning has found wide-ranging applications in communication systems, including RF energy harvesting circuits. Several studies have focused on developing optimal harvesting strategies for RFEH devices. For example, the approach in [21] introduced the Markov decision process (MDP) combined with an online algorithm to determine the most effective strategy for channel access whether for data transmission or energy harvesting, in cognitive radio networks. MDP has also been utilized to optimize power allocation in devices powered by energy harvesting [22], [23]. In [24], a protocol was introduced by the authors to facilitate RF energy harvesting for sensors in wireless sensor networks (WSNs) from both unintended and intended sources. The protocol utilizes two algorithms, namely a linear forecaster with a linear regression-based enhancer and artificial neural networks, to determine the optimal scheduling for RF energy harvesting. In [25], a decision policy based on the Bayesian multi-armed bandit (MAB) approach was developed to identify the optimal sub-band for harvesting.

Meanwhile, in [26], researchers focused on employing RFEH technology for charging the batteries of drones. They proposed an energy harvesting strategy to minimize drones' overall long-term power usage. These studies demonstrate the use of machine learning algorithms to enhance the efficiency and performance of RF energy harvesting systems. Notably, none of these studies utilized machine learning techniques for modeling the radio frequency signal itself, highlighting a potential avenue for future exploration in this field.

Previous studies present notable contributions in energy estimation for devices that harvest energy. In one study [27], a learning algorithm leveraging Bayes' theorem was employed in a hybrid access point (HAP) to estimate the energy consumption of wireless devices that harness energy from the HAP. In another study [28], researchers focused on the effect of human mobility on the energy storage medium, particularly in wearable devices. To address this, they introduced a Kalman filter-based predictor, which effectively estimated how much energy is accessible and facilitated energy exchange between capacitors of different sizes depending on the surrounding environment. In [29], an energy prediction algorithm utilizing the moving average approach was introduced for WSN nodes. This algorithm considered the historical data of the target node and the neighbouring nodes to predict energy levels. It is worth noting that while these works tackled the optimization of RFEH processes, none of them incorporated actual RF measurements in their methodologies.

Researchers have explored different learning techniques for optimizing the RF energy harvesting process. For instance, decision trees (DT) and linear regression (LR) were employed to predict RF energy at specific times and frequencies [30]. Researchers also utilized support vector machines (SVM) to forecast the highest Wi-Fi strength that would be available in different areas [31]. Additionally, four ML approaches including LR, SVM, DT, and random forest algorithm (RFA) were investigated to forecast the RF energy available in communication systems [32].

In conclusion, the literature review highlights the effectiveness of RF energy harvesting in various applications. Machine learning techniques have significantly optimized RF energy harvesting processes, including channel access, power allocation, and energy estimation strategies. However, there is still a research gap in utilizing machine learning to model the radio frequency signal. In addition, there is also a notable gap in exploring multi-band prediction techniques. To address these gaps, this study suggests a multi-band prediction approach to model the real-time RF energy as time series data and predict the energy in six frequency bands.

III. EXPERIMENTAL METHODS/METHODOLOGY

In the approach outlined in this paper, we follow multiple stages for model generation, as shown in Fig. 1. Firstly, we collect the raw RF energy signal. The second phase involves data preparation, including standardization and cleaning. The resulting processed data are then used for model training and evaluation.

Fig. 1. ML workflow for model generation.

A. Data Collection

The data collection process involved obtaining real-time measurements in multiple cellular frequency bands using software-defined radio (SDR) technology. SDR is a software-controlled radio that offers flexibility in functionality without requiring hardware changes. The block diagram of the SDR receiver is presented in Fig. 2. The SDR receiver captures RF waves through an antenna, converts them to IF using the RF Front End (RFFE), and processes them digitally with the analog to digital converter (ADC) and digital down converter (DDC) [33]. The universal software radio peripheral (USRP) N210 [34], presented in Fig. 3, is the hardware interface, connecting the RF spectrum to software via an Ethernet connection. GNU radio framework is used for baseband processing [35]. The RF signal is received by a printed circuit board (PCB) log periodic antenna operating between 850 and 6500 MHz. The signal measurement employs a conventional energy detection approach. This technique involves passing the signal through a band pass filter (BPF), squaring the result, and integrating it over a time interval [36].

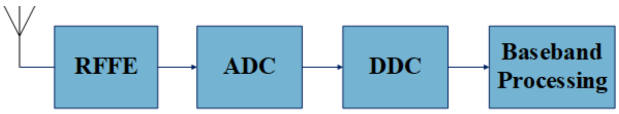

Fig. 2. SDR receiver block diagram.

Fig. 3. The USRP N210.

To ensure a comprehensive dataset, The RF signal was monitored across six cellular frequency bands spanning from 880 MHz to 2170 MHz. The range of bands includes 880–915 MHz, 925–960 MHz, 1710–1785 MHz, 1805–1880 MHz, 1920–1980 MHz, and 2110– 2170 MHz. Within each band, the frequency range was divided into smaller bins with a bandwidth of 0.2 MHz. Data points of the same bin were recorded at one-minute intervals.

B. Data Pre-processing

Pre-processing is the second step in our model, which involves two main tasks: data standardization and data cleaning. Data standardization ensures that the data are transformed to a standardized scale and facilitates consistent analysis. For data cleaning, we employ an anomaly detection algorithm to identify any outliers in the dataset. We utilized the Random Cut Forest (RCF) algorithm. This algorithm assigns an anomaly score to each data point. Lower scores indicate that the data points are considered normal, while higher scores indicate the presence of anomalous data points. By detecting and addressing these outliers, we obtain a clean and reliable dataset that can be used for subsequent stages such as model training and testing.

C. Model Architecture

The model architecture proposed for multi-band prediction was based on LSTM neural networks. LSTM is a Recurrent Neural Network (RNN) type that excels at capturing sequential patterns. It utilizes a memory mechanism where the output of the prior step is used as input to the current step, allowing it to retain critical information. LSTM is particularly effective in handling sequence data and addressing the issue of vanishing gradients, enabling it to capture long-term dependencies [37].

The architecture of the LSTM model consisted of multiple layers as shown in Fig. 4. The first is a 64-unit LSTM layer with the rectified linear unit (ReLU) activation function employed. This layer was followed by a 32-unit LSTM layer and a 16-unit LSTM layer, both also utilizing the ReLU activation function. Finally, a dense layer with linear activation was used to generate predictions for the energy levels in the six cellular frequency bands.

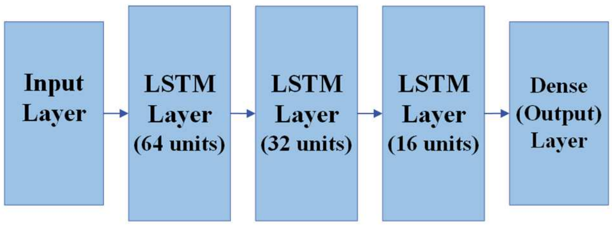

Fig. 4. Proposed LSTM architecture.

D. Model Training and Evaluation

The training procedure involved dividing the dataset into two subsets of 70% for training and 30% for testing. The training dataset was used to optimize the model's parameters, while the testing dataset was kept separate for evaluation. The model was trained using diverse data from different days to improve the model's ability to generalize and make accurate predictions on unseen data. Additionally, hyperparameter tuning was also performed to optimize the model's performance. This involved exploring different combinations of hyperparameters, such as learning rate, batch size, and number of hidden layers.

The model was trained using the adaptive moment (ADAM) optimization algorithm to ensure computational efficiency. The learning rate is set at 10^-3, and the mean square error is utilized as the loss function. To evaluate the performance of the model, we calculated the normalized root mean square error (NRMSE) for N number of time samples, expressed by (1) and (2), to represent the prediction error, where N is the number of training samples, y is actual output, and ŷ is the predicted output.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}{N}} \quad (1)$$

$$NRMSE = \frac{RMSE}{\max(y) - \min(y)}. \quad (2)$$

IV. RESULTS AND DISCUSSION

A. Proposed Model Performance

In this experiment, different sub-bands of the six bands were utilized for evaluation. The window size, which determines the number of previous data points used as history before predicting the following sample, was set to 10 samples. We predict the mean of the following 100 samples, representing one hundred-minute period. Performance results, presented in Table 1, describe the NRMSE for predicting RF energy samples using the LSTM model. Each value in the table represents the average error value of using different chunks in each band. Each chunk has 4096 samples of observations.

TABLE I. PERFORMANCE COMPARISON OF LSTM IN SIX BANDS IN TERMS OF NRMSE

Frequency Bands	Mean NRMSE				
	Chunk 1	**Chunk 2**	**Chunk 3**	**Chunk 4**	**Chunk 5**
880-915 MHz	0.0082	0.0062	0.0083	0.0063	0.0079
925-960 MHz	0.0093	0.0118	0.0119	0.0099	0.0088
1710-1785 MHZ	0.0115	0.0079	0.012	0.0076	0.0113
1805-1880 MHZ	0.0068	0.0126	0.0124	0.0067	0.0123
1920-1980 MHZ	0.01	0.0112	0.0103	0.0108	0.0105
2110-2170 MHZ	0.0096	0.0115	0.0115	0.0093	0.0116

The model demonstrates reasonable accuracy in predicting RF energy across different frequency bands. The average NRMSE values range from 0.0074 to 0.0107, indicating satisfactory prediction performance. The 880-915 MHz band shows relatively accurate predictions with NRMSE values ranging from 0.0062 to 0.0083 and an average NRMSE of 0.0074. The 925-960 MHz band exhibits slightly higher NRMSE values of an average of 0.0103. The 1710-1785 MHz, 1805-1880 MHz, 1920-1980 MHz, and 2110-2170 MHz bands display similar patterns, with NRMSE values ranging from approximately 0.007 to 0.012. The 880-915 MHz band recorded the highest average accuracy with 99.28% prediction accuracy.

Fig. 5 (a-f) illustrates the six bands' actual and predicted RF samples. For the 880-915 MHz band, the actual values range from 3.77E-07 to 3.82E-07 W, while the predicted values range from 3.76E-07 to 3.84E-07 W. The predicted values closely align with the actual values, indicating that the model performs well in accurately predicting RF energy in this band. The same pattern also continues for the other bands, with the predicted values consistently aligning with the actual values. This suggests the model performs well in predicting RF energy across different frequency bands.

B. Performance Comparison with Single-band Prediction

Table 2 compares the performance of multi-band prediction with single-band prediction in terms of NRMSE. In the multi-band prediction, the average NRMSE values range from 0.0074 to 0.0107, demonstrating relatively accurate predictions across the different frequency bands. On the other hand, in the single-band prediction, the NRMSE values range from 0.0062 to 0.0107.

TABLE II. PERFORMANCE COMPARISON BETWEEN MULTI-BAND AND SINGLE-BAND PREDICTION IN TERMS OF NRMSE USING THE LSTM MODEL.

Frequency Bands	NRMSE	
	Multi-band Prediction	**Single-band Prediction**
880-915 MHz	0.0074	0.0079
925-960 MHz	0.0103	0.0082
1710-1785 MHZ	0.0101	0.0107
1805-1880 MHZ	0.0102	0.0062
1920-1980 MHZ	0.0106	0.0097
2110-2170 MHZ	0.0107	0.0089

Based on the provided results, the multi-band and single-band predictions have similar overall performance in terms of NRMSE. However, it is worth noting that the single-band prediction achieved slightly lower NRMSE values in some frequency bands than the multi-band prediction. This suggests that focusing on individual frequency bands can improve prediction accuracy for those bands.

C. Performance Comparison with Previous Work

In this section, we compare the performance of LSTM against models identified in previous studies for predicting RF signals. Researchers in [32] reported an accuracy of 96.48% using LR, which was the highest and most stable among the four algorithms studied. In [30] an accuracy of 85% was recorded using LR, which outperformed DT. The study in [31] reported an accuracy of 83% using SVM. The literature analysis indicates that LR has the highest accuracy in previous studies. Therefore, we compare the performance of LSTM against LR. Fig. 6 presents the actual and predicted values using both LSTM and LR. It was observed that LSTM recorded a 5.5% lower NRMSE than LR in single-band prediction.

In multi-band prediction, Table 3 compares the NRMSE values between LSTM and LR models for predicting RF energy in different frequency bands. In all frequency bands, the LSTM model consistently achieves lower NRMSE values compared to the LR model. This suggests that the LSTM model outperforms LR in terms of prediction accuracy for RF energy in each band.

TABLE III. PERFORMANCE COMPARISON OF LSTM AND LR IN TERMS OF NRMSE

Frequency Bands	NRMSE	
	LSTM	**LR**
880-915 MHz	0.0074	0.1453
925-960 MHz	0.0103	0.1289
1710-1785 MHZ	0.0101	0.0919
1805-1880 MHZ	0.0102	0.1443
1920-1980 MHZ	0.0106	0.1771
2110-2170 MHZ	0.0107	0.1241

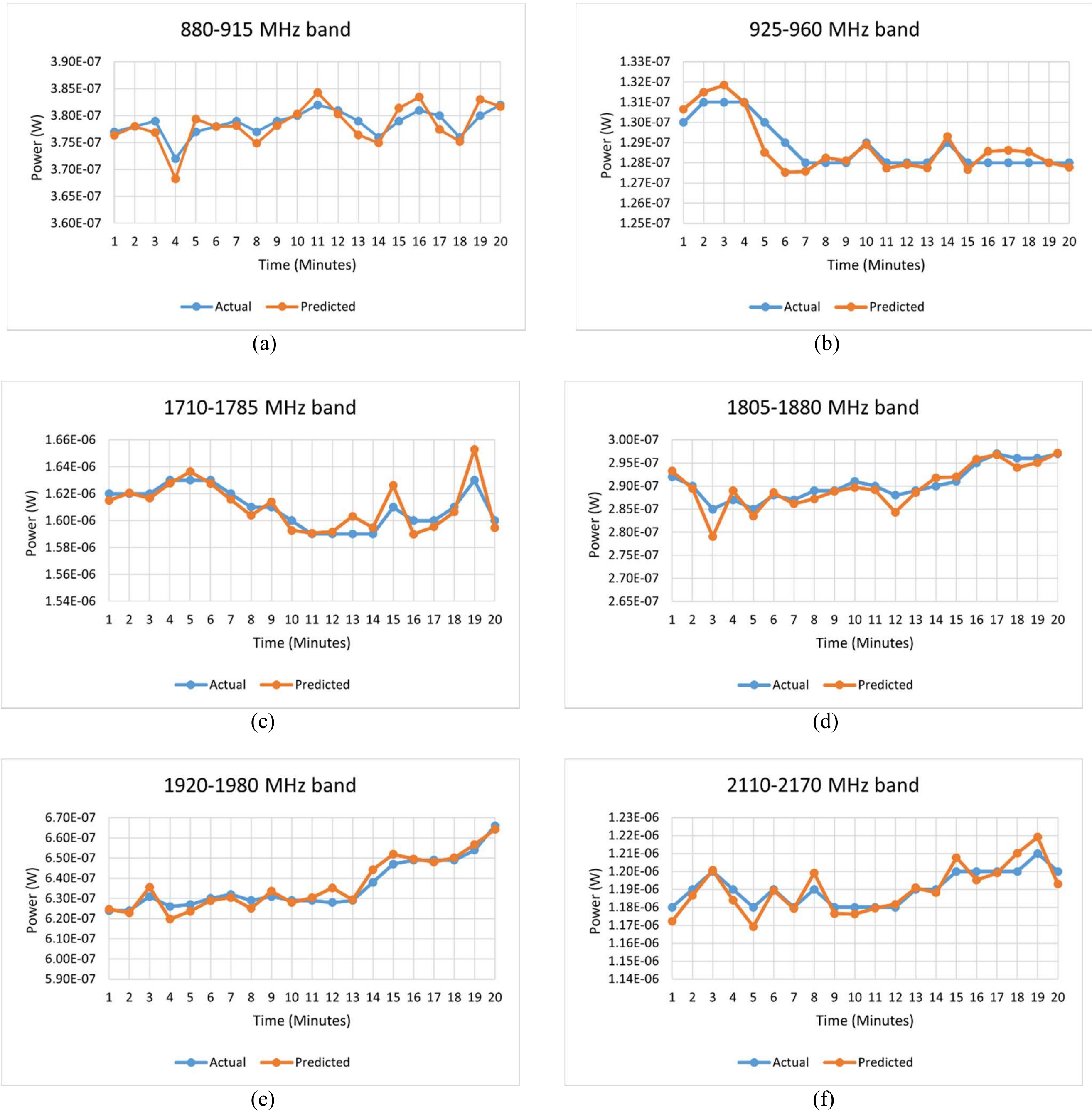

Fig. 5. Actual and predicted values using LSTM in six bands.

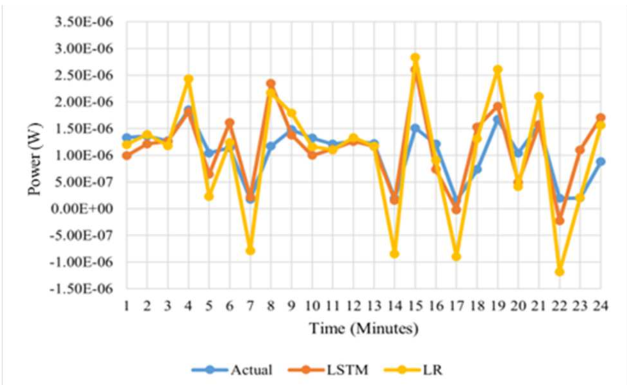

Fig. 6. Actual and predicted RF energy values using LSTM and LR.

V. CONCLUSION AND FUTURE WORK

In this study, we have proposed a complete workflow for developing a multi-band prediction approach to predict the energy of RF signals in six different frequency bands using LSTM. RF energy signal is measured at different frequency bands using SDR. We predict the mean of the subsequent hour and a half to ensure that the harvesting circuit consumes less power by making fewer harvesting decisions. The results indicate the effectiveness of the proposed approach in capturing the variations in RF energy across different bands by achieving accuracies above 98% in all bands. The comparison between multi-band prediction and single-band prediction indicates similar overall performance in terms of NRMSE, with slight advantages in prediction accuracy for specific bands in single-band prediction. To the best of our knowledge, no deep neural network model currently exists that can precisely forecast RF energy in multi-band systems in the field of RF energy harvesting. Accurately predicting RF energy is essential for optimizing energy harvesting circuits and powering wireless and low-powered devices without relying on batteries. The future work of this research is exploring model compression techniques to optimize the computational complexity of the model.

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